The Stock Market Effect of Air Pollution: Evidence from Finland and Hong Kong

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Abstract

Environmental stimuli have been found to affect people's moods, and through that, their risk aversion. Recent studies in the field of behavioral finance have documented an inverse relationship with one such stimulus – air pollution – and the corresponding domestic stock market returns. In this study, I investigate the existence of such "pollution effect" in the unique cities of Helsinki and Hong Kong. Using the particulate matter measurements from 2000 to 2016 as a proxy, I study the returns of various market and sector indices in relation to air pollution levels. The findings from numerous empirical tests show that an unhealthy air quality level in Helsinki negatively affects the following day's stock returns, especially for the Oil & Gas sector. The results suggest that air pollution is a behavioral factor with some connection to stock returns in Finland.

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1. Introduction

Traditional finance theories from the 20th century, such as the Capital Asset Pricing Model (Sharpe, 1964) take a quantitative approach to decision-making under uncertainty. This sort of consequentialist view[1] sees investors as rational beings capable of machine like processing of information, independent from influence of feelings. Since then, research in economic psychology and decision-making have proposed a more realistic approach, which assumes that feelings and emotions experienced during moment of decision-making affect the outcome (Loewenstein, Weber, Hsee, & Welch, 2001). Over the past few decades, behavioral finance researchers have also noticed the aforementioned development and begun to examine the role that mood determinants play in the minds of the investors. Empirical studies on various environmental stressors from weather to the body's biorhythm have been shown to have statistically and economically significant effects on stock returns (Lucey & Dowling, 2005). These findings are difficult to explain with traditional view of efficient markets (Fama, 1970).

One such variable is air pollution. Air pollution is a major health concern in industrialized countries and its adverse effects on human health have been thoroughly researched in medicine and environmental studies (World Health Organization WHO, 2003). Air pollution has also been used as a proxy for mood in recent behavioral finance literature investigating stock market returns in several countries. For instance, Levy & Yagil (2011) find an empirical relationship between air-quality index (AQI) levels and stock returns in the US that decreases as the distance between measurement station and stock exchange increases. Levy and Yagil (2013) later reproduce these results in other markets. Similarly, Lepori (2016) finds through a natural experiment that particulate matter (PM) levels in Milan are negatively correlated with Italian stock market returns when the exchange employs a trading floor. Additional studies from Turkey and China give further empirical evidence supporting a negative link between air quality and corresponding stock market returns (Demir & Ersan, 2016; Li & Peng, 2016).

However, the results of the studies showing an inverse correlation between air pollution and stock market returns have been somewhat inconsistent. Not only that, majority of the past research has focused on limited timeframes and overall market indices. Additionally, studies have centered on cities with relatively high pollution levels and exchanges with active trading

[1] As defined by Lowenstein *et al*. (2001)

floor communities, which are slowly fading as technology. Therefore, it is worthwhile to examine if the pollution effect is evident in Helsinki and Hong Kong: two cities with contrasting pollution levels and modern decentralized trading systems. Furthermore, it is of interest to investigate if the pollution influence varies across different industries and is still evident with fresh data.

In this paper, I analyze data from Finland and Hong Kong to determine if there is a relationship between daily air pollution levels and stock market returns. I extend upon past research and test whether earlier results hold across sectors, trading systems and time.

The rest of the paper is organized as follows: Section II explores past research and establishes a theory that links air pollution levels with stock market returns. The hypothesis will also be presented in this section. In Section III, I evaluate the data and methods used. Section IV states the results and robustness checks and Section V presents the conclusion.

2. Theoretical Background

For daily local pollution levels to affect stock market return on the same day, a link from local pollution levels to decision-making relevant for stock returns must exist. A number of studies in psychology exhibit that air pollution can have both direct and indirect effects on psychological and mental states (Bullinger, 1990). These in turn can lead to various negative physical, mental and mood changes. In the following section, I review past literature and exhibit connections between air quality and mood, mood and decision-making as well as mood and the stock market.

2.1 Air pollution and mood

The physical effects of air pollution have been widely studied, but focus has also been devoted to investigating its psychological effects. Bullinger (1989) documents psychological effects of air pollution in healthy residents though a time-series study. Her findings indicate that higher air pollution (SO2) levels produce impaired mood as well as increased stress with lags of up to 4-days. Similarly Rotko et al. (2002) conduct a survey study in six European cities (Athens, Basel, Milan, Oxford, Prague and Helsinki) and find that increases in particulate matter levels highly correlate with citizens perceived annoyance level. Zeidner and Schechter (1988) conduct a survey study in Israel and observe a link between air pollution and depression. They also note the perceived rather than objective level of pollution more accurately reflects the psychological effects of air pollution. Lundberg (1996) on the other hand studies air pollutions influence on behavior and links increased air pollution with heightened levels of anxiety. The majority of the above-cited studies imply that people experience more depressed mindsets, with slight variation from sample-to-sample, when exposed to acute levels of air pollution.

Numerous environmental toxins can interfere with the development and functioning of the nervous system and cause mental disorders with a wide range of psychiatric symptoms such as mood changes, personality changes, impaired memory, slower motor responses and other functional deviations. These toxins can cause shifts in the distributions of intelligence test scores, developmental delays, and accelerated aging (Weiss, 1988). Lepori (2016) points to findings in medicine that relate exposure to air pollution with increased levels of bodily cortisol levels. This is significant as psychological studies propose a negative relationship between cortisol levels in the body and sensation seeking levels (Rosenblitt et al., 2001). In the next section, an examination of how higher sensation seeking translates in to increased risk taking tendencies, will be conducted.

All the studies reviewed here report an observed relationship between air pollution and mood. As discussed next, mood has an impact on decision making, one type of which is an investment in the stock market.

2.2 Mood and decision-making

Psychologists have proposed many theories to explain influence of mood on behavior (Schwarz, 1989). One approach argues that the affective state experienced during the moment of decision will be biased by the mood being experienced, which will affect the outcome. This hold even in cases when there is no apparent connection between the cause of the prevailing mood and the decision in question (Lucey & Dowling, 2005). Loewenstein et al. (2001) propose a risk-as-feeling model for decisions involving uncertainty that accounts for the said possibility of mood misattribution. Lucey & Dowling (2005) summarize the premise of the model in that decisions involving cognitive evaluation will result in emotional reactions that influence the final decision. In other words, cognitive process, such as equity pricing begins a loop, which ends up influencing the outcome of the initial process. This is important when studies have found that people in positive moods tend to make optimistic judgements whereas people in negative moods are prone to pessimistic judgement (Isen, Shalker, Clark, & Karp, 1978). For instance, people in negative state of mind rate things such as life satisfaction lower than usual (Lucey & Dowling, 2005). Similarly, Isen et al. (1978) find that inducing a good mood on shoppers by giving them a gift results in better ratings for the shopping experience.

Various consumer behavior studies report comparable results with varied variables (see e.g. (Summers & Hebert, 2001). Slovic & Peters (2006) point that feelings motivate action towards things that reproduce feelings of similar direction. Bad mood can therefore increase risk aversion. This behavior is thought to have developed throughout human evolution as intuitive emotion based thinking was necessary for survival in primal situations. Experimental research in psychology relates depression and anxiety with higher levels of risk aversion measured by propensity of "sensation-seeking" (Zuckerman, 1984). Wong and Carducci (1993) documented that high sensation seekers displayed greater risk-taking tendencies in everyday financial matters than low sensation seekers. Zuckerman (1984) also links greater levels of depression and anxiety with reduced risk taking. This further bridges effects of environmental stressors on people with financial decision-making.

The stock market offers a natural setting to test the risk-as-feelings model proposed in psychology. Investment decisions and equity pricing are characterized by uncertainty. Hence, the individuals acting in the stock market provide a sample of interesting subjects to examine mood misattribution.

2.3 Environmental mood proxies and the stock market

The preceding sections have established a connection between air pollution and mood as well as mood and decision-making. In this section, I examine findings from the fields of economics and finance that have evaluated the economic consequences of various mood-related environmental stressors. Some of the mood proxies used include weather, amount of daylight, lunar-cycles and sports results.

Saunders (1993) first studied this relation by examining effects of local weather in New York City and the corresponding stock market returns. The study found significant negative correlation between the cloud cover over the city and daily stock market returns. Hirshleifer & Shumway (2003) later replicate these results in 26 countries. They find that morning sunshine is strongly related to stock returns during the trading day. Similarly, Kamstra et al. (2003) find a positive correlation with depression caused by seasonal variations in daylight and stock market returns. Edmans et al. (2007) use a novel mood variable of international soccer results to demonstrate the influence of mood misattribution in the context of the stock market. They document a significant market decline after soccer losses that varies with the importance of the match played. Likewise, Yuan et al. (2006) find that even when controlling for various anomalies, lunar phases are connected to stock returns. Their findings report that stock returns are lower on the days around full moon than on the days around new moon with a difference of magnitude of 3-5% per annum. Bialkowski et al. (2012) use the period of Ramadan to examine the mood effect and find significant results. The above cited studies are consistent with Kliger & Levy (2003) who by the use of US options and index price data show that bad mood is related with investors being less willing to tolerate risk, and vice versa

However, some studies have pointed out inconsistencies with the above results. For example, the results of Saunders (1993) seem to depend on how the null hypothesis is phrased, as well as on which sample period and returns are examined (Krmer & Runde, 1997; Trombley, 1997). In addition, Kelly & Meschke (2010) document that the observed effect is driven by an overlapping dummy-variable specification.

Based on psychological theory and earlier empirical insights, Li & Peng (2016) summarize three avenues of how air pollution can effect decision-making:

I. People are more pessimistic when they are in bad mood, which can be influenced by air pollution. This pessimism induces a tendency to find negative information more available and salient, which in turn translates to more negative evaluations of stocks.
II. Second, air pollution and the depression it can cause can both increase risk aversion. As stock market investments are characterized with risk, the result is a reduction in investment activity.
III. The resulting depression also leads to a lower investor elasticity of intertemporal substitution (EIS). In practice, this means that investors are less willing to substitute today's consumption for future consumption i.e. they are less willing to invest.

All of these three channel contribute towards a reduced demand in stock market that leads to a drop in stock prices.

2.4 The hypothesis

The above reviewed research from fields of psychology, medicine and financial economics form the basis for the hypothesis presented here. The cited studies have established that air pollution negatively influences mood, bad mood increases risk aversion and heightened risk aversion reduces stock market returns. In addition, they demonstrate concrete channels as to how air pollution can affect stock returns. Together they provide the grounds for the presence of "pollution effect" in the stock market, which indicates that air pollution negatively affects stock market returns. As such, I define the main hypothesis as follows:

H_1: *Stock market returns are negatively related to ambient air pollution.*

The hypothesis argues that increases in daily ambient air pollution levels lead to lower corresponding stock returns.

3. Data and Methods

3.1 Air Pollution Proxies

World Health Organization (WHO) defines air pollution as "contamination of the indoor or outdoor environment by any chemical, physical or biological agent that modifies the natural characteristics of the atmosphere." Air pollution levels are tracked at multiple measuring stations throughout the cities. The pollutants that cause public health concern include particulate matter (PM), carbon monoxide (CO), ozone (O_3), nitrogen dioxide (NO_x) and sulphur dioxide (SO_2). Li & Peng (2016) detail that PM is divided into two sub groups. $PM_{10,}$ which is particulate matter smaller than 10µm in diameter and, $PM_{2.5}$ which consists of particles smaller than 2.5µm in diameter. PM_{10} particulates can settle in the bronchi and lungs resulting in health problems. Even though people spend the majority of their time indoors, WHO (2006) maintains that outdoor levels of air pollutants are representative of population exposure.

In this paper, I focus on ambient air pollution, more specifically PM_{10} as the proxy for air pollution. The reason for this is twofold. First, PM is the most likely of the pollutants to cause health issues in human. Second, PM_{10} measurements are the more accurate and consistent between the two PM measures according to Helsinki Region Environmental Services Authority (HSY) and they also capture some of the influence of $PM_{2.5}$. Having consistent measurements is of utmost importance for the empirical analysis presented later as the testable samples vary across time and space.

I obtained daily particulate matter data for Helsinki and Hong Kong from January 1, 2000 to December 31, 2016. I use the 24-hour means to form an accurate proxy for regional air pollution exposure. The data for Helsinki was collected from two different measurement stations: the background station in Kallio and traffic station of Mannerheimintie[2]. I choose this station as they are within the closest proximity from the Helsinki Stock Exchange and financial district. According to HSY, the background station of Kallio most accurately represents the air pollution exposure in the inner-city area, whereas Mannerheimintie provides estimate for

[2] Measurement period for Mannerheimintie begins from 2005 when the station started operating.

air pollution levels in the dense downtown traffic. For the purposes of this study, I will devote most attention to Kallio station as the background more accurately depicts the air pollution levels investors are exposed to throughout the day. Similarly, I collect the Hong Kong PM data from The Hong Kong Government Environmental Protection Department (EPD). The data is extracted from Central/Western general station, as this is the closest background station relative to the Hong Kong Stock Exchange and Central financial district.

According to WHO (2006), the major share of TSP emissions at the European level is estimated to originate from "the combustion of solid fuels in small stoves in the residential and commercial sectors, followed by industrial emissions from energy combustion and manufacturing processes and from agricultural activities". HSY (2016) adds that for Helsinki road dust and combustion fuels have been main sources of PM. Likewise, EPD emphasizes the impact of diesel and other combustion fuels on the Hong Kong PM levels.

HSY (2016) cites commonly used threshold values defined by the European Union (EU) and WHO. EU uses a 40 µg/m^3 cut-off value for annual PM_{10} concentration whereas WHO is even stricter with a limit of 20 ug/m^3. The 24-hour mean PM_{10} threshold values used by HSY are 20 µg/m^3, 50 µg/m^3 and 100 µg/m^3 signifying satisfactory, tolerable and bad levels respectively. Figure 1 displays annual PM_{10} level development over the sample period. Overall, one can witness a downward trend in pollution levels, especially for Hong Kong and Mannerheimintie.

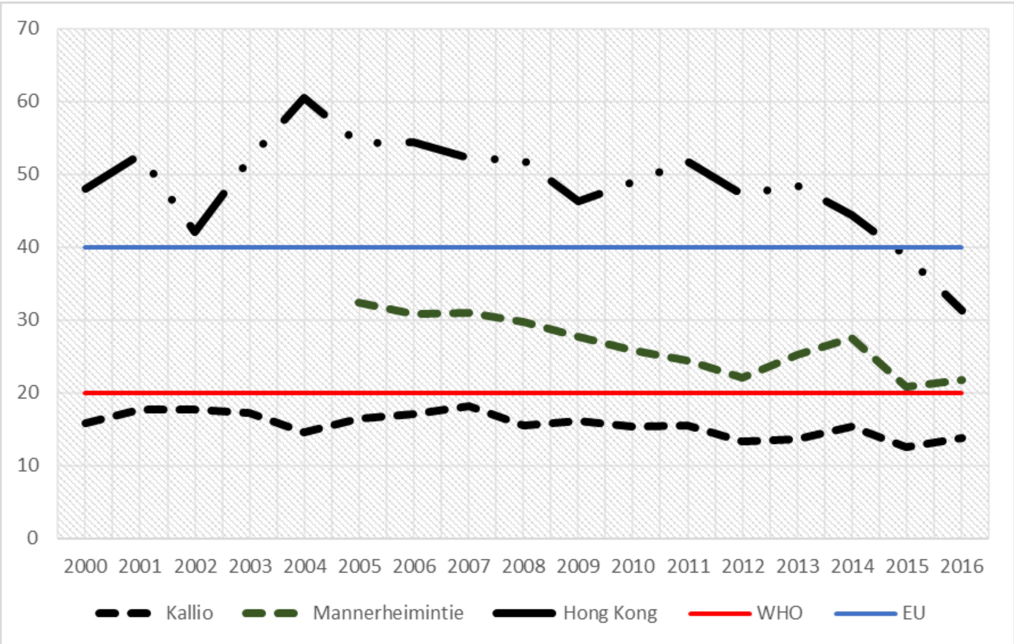

Figure 1. Development Trend of The Annual Particulate Matter Levels

Annual means for Kallio, however, have not seen as radical reductions. Table 1 provides descriptive statistics for daily PM_{10} levels. Henceforth, I will refer to PM_{10} simply as PM.

Table 1. Summary statistics for pollution measurement stations

Station	Period	Mean	Standard Deviation	Min	Max	Obs.	Unhealthy	% of Unhealthy
Kallio	4.1.2000 - 30.12.2016	15.55	9.20	0.00	115.55	4144	96	2.3 %
Mannerheimintie	3.1.2005 - 30.12.2016	26.61	16.25	4.21	184.18	2942	220	7.5 %
Hong Kong	3.1.2000 - 30.12.2016	48.65	29.36	7.00	636.00	4015	195	4.9 %

3.2 Stock Market Returns and Control Variables

I compile daily stock returns from Helsinki and Hong Kong Stock Exchange[3] from January 3, 2000 until December 30, 2016. The sample start date is driven by the availability of sector index data. I obtain Total Return Index (RI) from Thomson Reuters Datastream for the OMX Helsinki and Hang Seng overall indices. In addition to this, I compile RI for various sector indices in both exchanges. These include Basic Material, Financial, Industrial, Consumer Goods and Oil & Gas sectors. The Oil & Gas index for Helsinki begins from 2006. For Hong Kong, an official Hang Seng mainland Oil & Gas index begins from 2011. Therefore, I also form market value (MV) weighted return index beginning from 2001 from Petro China, Sinopec, and CNOOC[4]. I will refer to these as Oil & Gas (CALC) and Oil & Gas (HS) respectively. The Oil & Gas indices will be of special interest in the empirical analysis, as they represent companies that potentially contribute most to pollution levels (Levy & Yagil, 2013; Li & Peng 2016). However, it is worth noting that the Helsinki Oil & Gas index comprises of one company, Neste Oy, making its return more prone to fluctuate due to other than pollution factors.

From the RI I calculate daily percentage change for each index. This value will be used to represent daily stock returns. All of the indexes used account for dividends and reinvestments. Table 2 provides descriptive statistics for daily stock returns.

[3] For further information on the indices employed, refer to http://www.nasdaqomxnordic.com/indexes and https://www.hsi.com.hk/HSI-Net respectively.

[4] These companies are among the five largest oil companies in China and I speculate that they are the most relevant for Hong Kong. These companies are also included in the later established Hang Seng Oil & Gas index.

Table 2. Summary statistics of stock returns across indices

City	Period	Mean	Standard Deviation	Min	Max	Skeweness	Kurtosis	Obs.
Helsinki								
OMX Helsinki	3.1.2000 - 30.12.2016	0.01	1.83	-15.97	15.68	-0.13	6.93	4237
OMXH25	3.1.2000 - 30.12.2016	0.02	1.55	-8.52	9.73	-0.02	3.30	4237
Basic Materials	4.1.2000 - 30.12.2016	0.01	1.87	-10.65	11.96	0.06	2.69	4236
Financial	4.1.2000 - 30.12.2016	0.03	1.64	-15.34	11.75	-0.11	8.98	4236
Industrials	4.1.2000 - 30.12.2016	0.04	1.42	-7.98	9.72	-0.02	3.80	4236
Consumer Goods	4.1.2000 - 30.12.2016	0.04	1.36	-8.25	10.72	-0.03	4.88	4236
Oil & Gas	2.1.2006 - 30.12.2016	0.04	2.30	-8.25	23.69	0.36	6.67	2739
Hong Kong								
Hang Seng	3.1.2000 - 30.12.2016	0.02	1.52	-12.70	14.35	0.14	8.15	4189
Utilities	3.1.2000 - 30.12.2016	0.03	1.00	-13.93	14.77	0.19	25.14	4189
Financial	3.1.2000 - 30.12.2016	0.02	1.53	-13.53	17.32	0.29	11.54	4189
Commercial & Industrial	4.1.2000 - 30.12.2016	0.02	1.77	-12.54	14.72	0.08	5.77	4189
Consumer goods	4.1.2000 - 30.12.2016	0.03	1.51	-11.98	11.18	-0.32	5.74	4188
Oil & Gas (CALC)	1.3.2001 - 30.12.2016	0.22	1.65	-6.70	27.93	3.20	36.58	3903
Oil & Gas (HS)	8.3.2011 - 30.12.2016	-0.03	1.64	-8.58	9.04	0.16	3.13	1431

3.3 Methods

In order to test whether the level of air pollution influences stock returns, I employ the following methodology. First, I match pollution value with the corresponding stock return for each trading day. Second, I divide the trading days into two groups, Good and Unhealthy, based on the daily PM threshold values imposed by HSY. The cut-offs are as follows: 40 µg/m^3 for Kallio, 50 µg/m^3 for Mannerheimintie and 100 µg/m^3 for Hong Kong. I choose different cut-offs for the stations to as this allows the data to account for the differences in the average level of pollution, which stems from the nature of each location as described earlier. Based on these thresholds, the proportion of negative trading days in the sample is 2.3, 7.5, and 4.9 percentage for Kallio, Mannerheimintie and Hong Kong respectively.

The empirical methods used in the next section are focused around regression analysis and t-tests. Regression analysis of the following form will be used to evaluate the relationship between air pollution and stock returns:

$$r_t = \beta_0 + \beta_1 PM_{t-k} + \beta_2 Monday + \beta_3 January + \beta_4 r_{t-1} + \varepsilon_t \qquad (1)$$

, where, r_t is the daily stock return for the given index and PM_{t-k} represents the daily air pollution level. In the variables *t* denotes the day and *k* determines the lag between any given days returns and pollution. Similar to Lepori (2016) for majority of this study *k* takes the value of one. *Monday* and *January* are controlling variables that take the value of one on Mondays and in January respectively to control for weekend and January anomalies (French, 1980; Rozeff & Kinney, 1976). The variable r_{t-1} is used to purge the time series of stock returns from any intrinsic autocorrelations. The model and the control variables presented here are widely utilized in these sort of studies (see. e.g. Edmans, Garcia, & Norli, 2007; Kamstra, Kramer, & Levi, 2003; Levy & Yagil, 2011; Saunders, 1993). In addition, these studies often replace the continuous explanatory variable with a dummy to better illustrate the effect. Therefore, I also analyze the following model:

$$r_t = \beta_0 + \beta_1 Unhealthy_{t-k} + \beta_2 Monday + \beta_3 January + \beta_4 r_{t-1} + \varepsilon_t \qquad (2)$$

, where continuous variable PM_{t-k} is replaced with dummy variable $Unhealthy$ that takes the value of one in days for unhealthy pollution levels and zero otherwise. For both models, the expected signs of the ordinary lease squared (OLS) coefficients are $\beta_1 < 0$, $\beta_2 < 0$, $\beta_3 > 0$, and $\beta_4 = 0$, respectively, based on Hypothesis 1, the Monday effect, the January effect, and the market efficiency hypothesis of zero serial correlation of returns. For robustness, purposes I estimate Models (1) and (2) with varied indices and prolonged pollution levels. In such cases, prolonged exposure is measured by the following three-day moving average[5]:

$$PM_t^{Average} = \frac{1}{3}\sum_{j=1}^{3} PM_{t-j} \qquad (3)$$

Similarly, to Levy & Yagil (2011) I will also use t-tests to provide an order of magnitude for potential relationship. This is done, as the levels of the relationship between air pollution and stock returns may not be very high. The t-tests, which are commonly used in equity return studies, will measure the differences between Good sample and Unhealthy sample proposed earlier in terms of the mean return. The t-static is calculated as:

$$t_{means} = (\bar{r}_{Good} - \bar{r}_{Unhealthy})/(\sigma^2_{good}/n_{good} + \sigma^2_{Unhealthy}/n_{Unhealthy})^{1/2} \qquad (4)$$

, where $\bar{r}$ and σ^2 are the mean and variance of the daily stock rate of return, and n is the number of trading days in each group.

[5] The moving average includes weekend values to better measure prolonged exposure.

4. Results

4.1 Initial t-test

I begin the empirical analysis with the t-test for all three measurements stations. The tests are performed in respects to the same day (*t)* and preceding day (*t-1)* pollution exposure. The mean daily return for each stock index is given as the average of the daily returns across all trading days in the pollution subgroup. Table 3 presents the findings for Model (1) with all seven indices in Helsinki and Hong Kong.[6]

Table 3. Summary statistics of the mean daily stock returns measured by the daily PM levels in Helsinki and Hong Kong.

	One day lagged pollution				Same day pollution			
Stock index	**Mean daily return (%)**							
	Good	**Unhealthy**	**UMG**	**p-value**	**Good**	**Unhealthy**	**UMG**	**p-value**
<u>*Kallio*</u>								
OMX Helsinki	0.030	-0.661	-0.691***	0.002	0.008	-0.004	-0.012	0.940
OMXH25	0.033	-0.499	-0.532***	0.003	0.013	0.052	0.040	0.767
Basic Materials	0.020	-0.308	-0.328*	0.086	0.005	0.042	0.037	0.845
Financial	0.043	-0.293	-0.337*	0.095	0.027	0.018	-0.009	0.958
Industrials	0.044	-0.153	-0.197	0.148	0.029	0.203	0.174	0.111
Consumer Goods	0.043	0.022	-0.021	0.865	0.039	0.066	0.027	0.796
Oil & Gas	0.053	-0.750	-0.803***	0.009	0.028	0.130	0.103	0.760
<u>*Mannerhimintie*</u>								
OMX Helsinki	0.027	-0.037	-0.064	0.568	0.117	-0.010	-0.128	0.690
OMXH25	0.042	-0.051	-0.093	0.405	0.116	0.032	-0.084	0.945
Basic Materials	0.033	-0.101	-0.134	0.357	0.092	-0.104	-0.196	0.250
Financial	0.038	0.107	0.069	0.639	0.137	0.130	-0.007	0.496
Industrials	0.057	0.033	-0.024	0.832	0.171	0.089	-0.083	0.704
Consumer Goods	0.047	-0.055	-0.102	0.343	0.082	-0.017	-0.099	0.523
Oil & Gas	0.057	-0.133	-0.190	0.287	0.615	0.119	-0.496	0.613
<u>*Hong Kong*</u>								
Hang Seng	0.023	-0.100	-0.123	0.301	-0.031	-0.111	-0.142	0.307
Utilities	0.035	-0.052	-0.087	0.235	0.021	-0.054	-0.033	0.205
Financial	0.026	-0.107	-0.134	0.266	0.021	-0.145	-0.124	0.197
Commercial & Industrial	0.022	-0.060	-0.082	0.548	-0.044	-0.089	-0.133	0.460
Consumer goods	0.029	-0.057	-0.085	0.464	-0.277	0.118	-0.158	0.383
Oil & Gas (CALC)	0.216	0.337	0.121	0.482	0.211	0.366	0.577	0.406
Oil & Gas (HS)	-0.024	0.084	0.061	0.555	-0.016	-0.190	-0.206	0.345

Notes: The time period covered is 2000-2016. However, due to data availability Mannerheimintie sample begins from 2005. Similarly, the index start dates vary slightly. Refer to Table 2 for specific periods. UMG denotes the Unhealthy minus Good return difference. Kallio and Hong Kong (Central) are background stations, whereas Mannerheimintie is a traffic station. P-value for Model 4 is reported and * denotes statistical significance of 10%, **denotes statistical significance of 5% and ***denotes statistical significance of 1%.

[6] The Helsinki *Basic Materials* and Hong Kong *Utilities* as well as Industrials and Commercial & Industrials indices are comprised with similar companies. For further detail of the indices used refer to websites in footnote three.

The findings in the left hand side of Table 3 indicate that the Unhealthy minus Good (UMG) mean daily return difference is negative for all indices with Kallio one day lagged pollution measurements. Apart from Industrials and Consumer Goods indices, this difference is also statistically significant. The difference seems to be especially strong for the Oil & Gas index with the difference for the mean daily returns being 0.803 and it is statistically significant at the 1% level. In addition, the overall stock market index OMX Helsinki and OMXH25 both report relatively large UMG values, which both are significant at the 1% level. The index showing the least reaction to pollution levels is Consumer Goods.

The majority of the Mannerheimintie and Hong Kong results are also similar, pointing towards a negative UMG. However, they never reach statistical significance. Interestingly, the Hong Kong Oil & Gas indices report positive, albeit insignificant, UMG values. One possible explanation for this is the fact that, although listed in the Hong Kong exchange, the companies forming the indices are based in mainland China. Therefore, investors may not form as strong a connection with the companies in question and the corresponding pollution levels in Hong Kong. Based on these findings we can reject the null hypothesis of equal means for the Good and Unhealthy subgroup in Kallio with a 10% confidence level. The findings also imply preliminary support for Hypothesis 1.

As for the right hand side of the table, where returns are grouped by the same day PM levels, the results are more inconsistent. For Kallio station, the returns are unexpectedly larger on Unhealthy as opposed to Good days. On the other hand, Mannerheimintie and Hong Kong stations report values that are more negative than they did when the grouping was done with lagged pollution levels. As the pollution levels from these stations are greatly higher than those of Kallio (see Table 1), I speculate that the level of pollution influences the speed the “pollution effect” is transmitted to investors. The fact that these two stations are also closer to the financial centers of their respective cities further supports the deduction. The people influencing the stock market would be exposed to these levels throughout their commute and workday. However, the background station of Kallio better depicts the long-term exposure levels these people face at their home and inside at work. In addition, I want to point out that none of the results on the right side of the table are statistically significant. Therefore, the deduction described above is just one possible explanation and further evidence is needed.

Overall, the results in Table 3 imply a link between lagged pollution levels measured by background station in Kallio and the daily stock returns. Therefore, the rest of the empirical analysis in this paper will be focused on the lagged pollution levels measured at the Kallio background station.

4.2 Regression analysis – continuous pollution proxy

The t-test provides a rudimentary way to estimate the "pollution effect" through differences in sample means. However, to find further evidence, I perform the regression analysis of Model (1) for Kallio with *t*-1 continuous pollution levels. Table 4 summarizes the results for all seven indices.

Table 4. Daily Stock Returns and Air Pollution: Kallio PM(t-1) as Pollution Proxy

The table shows the mean daily stock returns (%) in relation to one-day lagged continuous PM levels in Kallio. Dependent variables are the various sector indices. Jan and Mon are dummies controlling for January and Monday effect. $r_{(t-1)}$ is the unique one-day lagged return for each corresponding index controlling for autocorrelation. t-statistics are stated in parentheses. *, ** and *** represent significance at the 10 %, 5 %, and 1 % level, respectively.

	Dependent variable: Daily Index Return r_t (in percentage)						
	OMXHKI (1)	OMXH25 (2)	BasicMats (3)	Financial (4)	Industrial (5)	ConsumerGds (6)	OilGas (7)
PM$_{t-1}$	-0.004	-0.003	-0.001	-0.002	-0.001	0.0001	-0.006
	(-1.275)	(-1.177)	(-0.201)	(-0.801)	(-0.555)	(0.029)	(-1.177)
Jan	-0.003	-0.017	-0.055	-0.005	0.091	0.021	0.273*
	(-0.028)	(-0.190)	(-0.518)	(-0.054)	(1.132)	(0.266)	(1.665)
Mon	-0.052	-0.047	0.002	-0.035	-0.031	-0.097*	-0.108
	(-0.735)	(-0.772)	(0.029)	(-0.544)	(-0.568)	(-1.849)	(-0.971)
r_{t-1}	-0.0004	0.030*	0.072***	-0.012	0.050***	0.027*	-0.010
	(-0.028)	(1.902)	(4.635)	(-0.778)	(3.193)	(1.753)	(-0.489)
Constant	0.087	0.079	0.027	0.079	0.058	0.059	0.129
	(1.451)	(1.572)	(0.439)	(1.486)	(1.260)	(1.338)	(1.368)
Observations	4,144	4,144	4,142	4,142	4,142	4,142	2,667
Adjusted R^2	-0.0004	0.0004	0.004	-0.001	0.002	0.001	0.001
Residual Std. Error	1.835 (df = 4139)	1.551 (df = 4139)	1.860 (df = 4137)	1.640 (df = 4137)	1.410 (df = 4137)	1.351 (df = 4137)	2.301 (df = 2662)

The results presented in Table 4 provide more evidence for the initial story told by the t-test: aside from Consumer Goods index, all other indices report negative coefficients for β_1 ranging from -0.001 to -0.006. Again, the returns in Oil & Gas index seems to react most to fluctuation in daily PM levels. A one standard deviation increase (9.2 ug/m^3) in PM_{t-1} results in around 0.06% lower returns in the the Oil & Gas index the following day. However, it is worth noting that none of the PM_{t-1} coefficients are statistically significant. In addition, the coefficients are relatively minor in economic terms. The January effect is also significant at the 10% level for the Oil & Gas index, whereas Monday effect is present for Consumer Goods index at 10% significance level. Some autocorrelation seems to be present for the returns of Basic Materials, Industrial and Consumer Goods indices. Based on the results in Table 3 and 4, I can conclude that the "pollution effect" seems to be the least pronounced for the Consumer Goods and Industrial sectors. Despite the aforementioned caveats, I would like to emphasize that all but one of the PM_{t-1} coefficients above indicate a negative link between air pollution levels and following day stock returns.

4.3 Prolonged exposure to air pollution

Based on the medical and psychological research presented in Section 2, I follow the speculation of Lepori (2016), and test whether prolonged exposure to high levels of air pollution adds to each other. In forming the theory, Lepori points to reviews in medicine, which argue that a multi-day moving average best depicts air pollutions' effect on humans. Following this reasoning, I construct a three-day moving average of the continuous PM levels using the formula presented in Model (3). After this, I re-estimate the regression in Model (1) using the said average. Table 5 shows the summary statistics for the results:

Table 5. Daily Stock Returns and Air Pollution: Prolonged Exposure (PM AVG)

The table provides results summary for prolonged exposure regression. $r_{(t-1)}$ is the unique one-day lagged return for each corresponding index controlling for autocorrelation. The sample period is 2000-2016. t-statistics are stated in parentheses. *, ** and *** represent significance at the 10 %, 5 %, and 1 % level, respectively.

	Dependent variable: Daily Index Return in r_t (in percentage)						
	OMXHKI	OMXH25	BasicMats	Financial	Industrial	ConsumerGds	OilGas
PM_AVG	-0.002	-0.002	-0.001	-0.004	-0.002	0.0001	-0.008
	(-0.443)	(-0.662)	(-0.185)	(-1.037)	(-0.634)	(0.049)	(-1.260)
Jan	-0.002	-0.014	-0.059	-0.013	0.080	0.013	0.272^{*}
	(-0.017	(-0.158)	(-0.563)	(-0.139)	(1.011)	(0.170)	(1.686)
Mon	-0.053	-0.052	-0.001	-0.047	-0.038	-0.101^{*}	-0.111
	(-0.751)	(-0.862)	(-0.008)	(-0.740)	(-0.692)	(-1.938)	(-1.006)
r_{t-1}	0.001	0.030^{*}	0.070^{***}	-0.011	0.051^{***}	0.027^{*}	-0.010
	(0.069)	(1.930)	(4.537)	(-0.726)	(3.292)	(1.753)	(-0.517)
Constant	0.043	0.059	0.028	0.097	0.067	0.056	0.149
	(0.648)	(1.052)	(0.410)	(1.632)	(1.304)	(1.152)	(1.420)
Observations	4,214	4,214	4,212	4,212	4,212	4,212	2,718
Adjusted R^2	-0.001	0.0002	0.004	-0.0005	0.002	0.001	0.001
Residual Std. Error	1.833 (df = 4209)	1.552 (df = 4209)	1.863 (df = 4207)	1.639 (df = 4207)	1.413 (df = 4207)	1.352 (df = 4207)	2.298 (df = 2713)

The results are strikingly similar to those presented in Table 4 for the one-day lagged pollution proxy. Again, most of the indices report negative coefficients for the pollution term. However, aside from the Oil & Gas sector, the "pollution effect" seems to weaker and less statistically significant than with the one-day lagged pollution proxy. These results are somewhat inconsistent with Lepori (2016), who finds that the coefficient for the prolonged exposure variable is slightly stronger than for the simple one-day lagged pollution variable. However, Lepori points out that there is not enough statistical evidence to conclude that the impact of air pollution on trading decisions would be stronger when air pollution levels have been high for a few days in a row.

4.4 Regression analysis – Unhealthy dummy variable as proxy

To better comprehend the relationship between air pollution and stock returns, I estimate the regression of Model (2), where the continuous pollution proxy is replaced with a dummy variable dividing pollution levels to Good and Unhealthy. The grouping is done by combining the trading days for which PM is at a certain level with the corresponding daily stock return. For Kallio the cut-off level is the earlier stated 40 µg/m^3. This simple econometric approach has been employed in numerous empirical studies in finance to reduce the statistical white noise (Levy & Yagil, 2011). As the tests in the above subsection indicate that the pollution effect is most evident for the one-day lagged pollution levels in Kallio, I estimate the regression of Model (3) with a *k* value of one. The summary statistics for the regression are shown in Table 6.

Table 6. Daily Stock Returns and Air Pollution: Unhealthy$_{t-1}$ dummy variable

Unhealthy$_{t-1}$ is a dummy variable representing air pollution during sample period 2000-2016. r_{t-1} is the unique one-day lagged return for each corresponding index controlling for autocorrelation. t-statistics are stated in parentheses. *, ** and *** represent significance at the 10 %, 5 %, and 1 % level, respectively.

	Dependent variable: Daily Index Return r_t (in percentage)						
	OMXHKI	OMXH25	BasicMats	Financial	Industrial	ConsumerGds	OilGas
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unhealthy$_{t-1}$	-0.695***	-0.537***	-0.336*	-0.341**	-0.200	-0.026	-0.783**
	(-3.668)	(-3.354)	(-1.750)	(-2.009)	(-1.373)	(-0.189)	(-2.335)
Jan	-0.009	-0.021	-0.062	-0.007	0.090	0.020	0.274*
	(-0.087	(-0.244	(-0.582	(-0.078	(1.119	(0.256)	(1.673)
Mon	-0.057	-0.050	-0.0003	-0.037	-0.032	-0.097*	-0.109
	(-0.795)	(-0.827)	(-0.004)	(-0.574)	(-0.590)	(-1.853)	(-0.976)
r_{t-1}	-0.0004	0.030*	0.072***	-0.012	0.050***	0.027*	-0.009
	(-0.026)	(1.919)	(4.642)	(-0.781)	(3.219)	(1.753)	(-0.478)
Constant	0.042	0.044	0.025	0.053*	0.042	0.061**	0.052
	(1.254)	(1.570)	(0.754)	(1.772)	(1.638)	(2.471)	(1.001)
Observations	4,144	4,144	4,142	4,142	4,142	4,142	2,667
Adjusted R^2	0.002	0.003	0.005	0.0002	0.002	0.001	0.002
Residual Std. Error	1.832 (df = 4139)	1.549 (df = 4139)	1.859 (df = 4137)	1.639 (df = 4137)	1.410 (df = 4137)	1.351 (df = 4137)	2.299 (df = 2662)

The results indicate that the impact of unhealthy air quality variable is negative and statistically significant for all indices, aside from Industrial and Consumer Goods. The OLS coefficients for β_1 range anywhere from -0.026 to -0.783 between the indices. As in the previous tests, Oil & Gas index is showing the most reaction to fluctuations in PM levels. To put things to perspective, if the air pollution is unhealthy the following day's stock returns are approximately 0.7 and 0.8 percent lower for OMX Helsinki and Oil & Gas indices respectively. The findings shown here tell a compelling story in support of Hypothesis 1. Even, though January effect is also statistically significant for the Oil & Gas index, it is not strong enough to dismiss the "pollution effect". In addition, no significant Monday effect or autocorrelation between returns is present for the two indices showing the most evidence of "pollution effect". Based on these and the previous results, I conclude that no "pollution effect" is evident for the Consumer Goods sector nor the Industrials sector. The findings here are also interesting in relation to those of Lepori (2016) who reported no relationship between PM levels and stock returns when the stock exchange employed a decentralized floorless system. As Helsinki Exchange has no centralized trading floor during the sample period, I estimate that the role of the trading floor is not as strong as expected by Lepori (2016) and that market agents are effected elsewhere. The results also suggest that other financial institutions aside from the actual stock exchange play an important role in today's stock market.

4.5 Subsample analysis

To test if the "pollution effect" implied by previous tests is driven by the values at the turn of the millennia or the ones towards the end of the sample period, I construct three subsamples from the entire period. The sample periods are 3.1.2000 - 30.12.2004, 3.1.2005 - 30.12.2010 and 3.1.2011 – 30.12.2016[7]. I estimate the regression described in Model (1) for all of these periods using the OMX Helsinki and Oil & Gas index when available. I use the continuous pollution proxy for the analysis as the number of unhealthy days varies greatly across subsamples making the comparison less statistically feasible.

[7] The first subsample is only five years to make the following two subsamples more comparable with Mannerheimintie.

Table 7. Daily Stock Returns and Air Pollution: Subsample Analysis

The table presents summary statistics for the subsample analysis using $PM_{(t-1)}$ *as pollution proxy.* $r_{(t-1)}$ *is the unique one-day lagged return for each corresponding index controlling for autocorrelation. t-statistics are stated in parentheses. *, ** and *** represent significance at the 10 %, 5 %, and 1 % level, respectively.*

	2000 - 2004	*2005 – 2010*		*2011 - 2016*	
	OMXHKI	OMXHKI	OilGas	OMXHKI	OilGas
	(1)	(1)	(7)	(1)	(7)
PM_{t-1}	-0.010	-0.003	-0.009	0.002	0.002
	(-1.257)	(-0.668)	(-1.431)	(0.340)	(0.260)
Jan	-0.155	-0.004	0.097	0.118	0.425*
	(-0.575)	(-0.029)	(0.396)	(0.983)	(1.923)
Mon	-0.050	0.073	0.050	-0.175**	-0.237
	(-0.272)	(0.720)	(0.303)	(-2.138)	(-1.580)
r_{t-1}	-0.016	-0.009	-0.013	0.067**	-0.010
	(-0.554)	(-0.354)	(-0.440)	(2.573)	(-0.365)
Constant	0.165	0.070	0.100	0.016	0.032
	(1.064)	(0.865)	(0.757)	(0.203)	(0.387)
Observations	1,227	1,465	1,215	1,452	1,452
Adjusted R^2	-0.001	0.012	0.005	0.007	0.001
Residual Std. Error	2.585 (df = 1222)	1.824 (df = 1220)	1.531 (df = 1220)	0.970 (df = 1220)	0.951 (df = 1220)

The results in Table 7 tell an interesting story. The β_1 coefficient for OMX Helsinki ranges from -0.010 in the earliest subsample to 0.002 to in the most recent subsample. Albeit none of the β_1 coefficients reach statistical significance, the coefficients are even less significant in the 2011 – 2016 subsample. The Oil & Gas index presents similar results. The "pollution effect" seems to have reduced as the actual pollution levels have gone down as is shown in Figure 1. However, at the same time the presence of foreign investors in Finland has gone down from 71% in 2000 to approximately 50% in 2016 (Keloharju & Lehtinen, 2015). It would make sense that the foreign investors are not affected by the local air pollution levels in Helsinki and that the "pollution effect" would be stronger when the proportion of local investors is relatively larger. One possible explanation is the fact that foreign investors were mainly interested in Nokia, whose peak and later demise coincides with the sample period. As such, I speculate the main rational behind the results is the reduction in overall pollution levels.

4.6 Robustness checks

In the previous section, I found some evidence supporting Hypothesis 1, especially for one-day lagged effects in Kallio and the Oil & Gas index. In addition, some concerns of endogeneity arise due to the connection between economic activity and the air pollution levels. However, the fact that the pollution measurement station represents the exposure of the inner-city area, limits this issue.

In this section, I further test Hypothesis 1 by estimating a logit regression for the lagged pollution levels as well as looking at evidence in Hong Kong and Mannerheimintie.

4.6.1 Logit regression

Lepori (2016) employs a logit regression to test the “pollution effect”. In the spirit of this, I also test whether it is the sign rather than the magnitude of stock returns that is affected by pollution levels. Therefore, I estimate the following regression for the one-day lagged pollution variables:

$$P(R_t > 0) = \frac{e^{\mu_1 PM_{t-1} + \mu_2 January + \mu_3 Monday + \mu_3 R_{t-1}}}{1 + e^{\mu_1 PM_{t-1} + \mu_2 January + \mu_3 Monday + \mu_3 r_{t-1}}} \tag{5}$$

, where R_t is the binary return variable taking the value of one when the corresponding index returns are positive.[8] The summary results for Model (5) with one-day lagged continuous and dummy variable are presented in Table 8.

[8] Other variables are as defined before.

Table 8. Daily Stock Returns and Air Pollution: Logit Regression

*The table presents summary reports of Model (5) with sample period 2000-2016. Standard deviations are stated in parentheses. *, ** and *** represent significance at the 10 %, 5 %, and 1 % level, respectively. Note: Oil & Gas sample begins in 2005.*

	Dependent variable: Index Returns R_t (in percentage)			
	OMXHKI	OilGas	OMXHKI	OilGas
	(1)	(2)	(3)	(4)
PM_{t-1}	-0.005	-0.002		
	(0.003)	(0.004)		
$Unhealthy_{t-1}$			-0.337	-0.694**
			(0.208)	(0.309)
Jan	-0.012	0.096	-0.007	0.089
	(0.114)	(0.143)	(0.114)	(0.142)
Mon	-0.042	0.085	-0.043	0.084
	(0.078)	(0.097)	(0.078)	(0.097)
R_{t-1}	0.075	-0.062	0.075	-0.060
	(0.062)	(0.078)	(0.062)	(0.078)
Constant	0.120*	0.042	0.053	0.020
	(0.073)	(0.090)	(0.049)	(0.059)
Observations	4,143	2,667	4,143	2,667
Log Likelihood	-2,866.973	-1,847.534	-2,866.632	-1,844.985
Akaike Inf. Crit.	5,743.947	3,705.068	5,743.264	3,699.969

For the continuous variable, very little relationship is evident between air pollution and the sign of the following day's index returns. However, when estimated with the dummy variable the coefficient for pollution effect is significant at the 5% level for the Oil & Gas index. The results in the left side of the table are in line with those of Lepori (2016) as Helsinki Stock Exchange does not have a trading floor. Despite this, however, investors' mood seems to be affected when the air pollution reaches unhealthy level as is evident in the right side of the table, which is somewhat inconsistent with Lepori (2016).

4.6.2 Evidence from Hong Kong and Mannerheimintie

The regression analyses have focused on the background measurement station of Kallio, as it was the only one showing significant results in the initial t-test. However, I also estimate Model (2) with k value of one for the Hong Kong (Central) background measurement station and Mannerheimintie traffic station. The summary results are presented in the Appendix. The results are expectedly in line with the t-test results: Majority of the β_1 coefficient have a negative sign but never statistically different from zero. One possible explanation for this in the case of Hong Kong is that people have gotten accustomed to high pollution levels raising their internal state (Cabanac, 1971). As such, people's moods do not react to changes between good and unhealthy pollution levels, because the good is not that good to begin with. In the case of Mannerheimintie, the measurements might be affect too much by nearby traffic giving an inaccurate proxy for the actual pollution exposure the people face.

The various empirical tests have given initial support in favor of hypothesis 1 in Kallio when using the dummy variable proxy for pollution. However, I have not controlled for the various other environmental stressors, such as rainfall, which might reduce the "pollution effect". In addition, the economic significance of the results might be trivial after accounting for transaction costs. Taking all of the aforementioned concerns and limitations into account, it would be premature to reject the null hypothesis of no "pollution effect".

5. Conclusion

Past research in the field of finance has provided evidence of a relationship between the air pollution levels in the city housing the stock exchange and domestic stock market returns, especially when the exchange in question has an active trading floor community. In this thesis, I have studied if such relationship is present in the decentralized Helsinki and Hong Kong Stock Exchanges.

Analyzing a sample of pollution levels and the corresponding daily stock market returns spanning over two decades, I have found initial evidence that the lagged air pollution levels in Helsinki negatively influence the following day's stock market returns. This "pollution effect" is evident only when using air pollution measurements from the background station of Kallio. In addition to being statistically significant, the effect is consistent across majority of the sectors, with Oil & Gas sector showing most evidence in line with the prediction.

A subsample analysis of the period reveals that the “pollution effect” is mostly driven by the high air pollution levels in the beginning of the sample period and it has decreased as pollution levels have gone down. The results imply tentative support for Hypothesis 1 and somewhat contradict the earlier findings of Lepori (2016) who suggests that an active trading floor community is the mediating factor between air pollution levels and stock returns.

Potential future research could look further into what the mediating factor between air pollution and the stock returns is. Additionally, examining the presence of “pollution effect” in other asset classes could provide robustness for the previous results to find out if an actual violation of the Efficient Market Hypothesis exists.

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7. Appendix

Table 9 Daily Stock Returns and Air Pollution: Mannerheimintie

The table presents summary reports of Model (2) with sample period 2005-2016. t-statistics are stated in parentheses. *, ** and *** represent significance at the 10 %, 5 %, and 1 % level, respectively. Note: Oil & Gas sample begins in 2005.

	Dependent variable: Daily Index Returns (r_t)						
	OMXHKI	OMXH25	BasicMats	Financial	Industrial	ConsumerGds	OilGas
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unhealthy_{t-1}	-0.061	-0.094	-0.127	0.066	-0.020	-0.098	-0.173
	(-0.614)	(-0.898)	(-0.957)	(0.562)	(-0.181)	(-0.939)	(-0.972)
jan	0.031	-0.002	0.001	-0.032	0.082	0.021	0.265
	(0.323)	(-0.022)	(0.005)	(-0.279)	(0.772)	(0.205)	(1.633)
mon	-0.044	-0.043	-0.050	-0.093	-0.033	-0.105	-0.079
	(-0.680)	(-0.634)	(-0.576)	(-1.195)	(-0.455)	(-1.520)	(-0.711)
r_{t-1}	0.023	0.024	0.053^{***}	0.0004	0.043^{**}	0.038^{**}	-0.008
	(1.243)	(1.325)	(2.891)	(0.022)	(2.366)	(2.089)	(-0.394)
Constant	0.032	0.050	0.041	0.059	0.054	0.064^{*}	0.050
	(1.042)	(1.525)	(0.985)	(1.602)	(1.562)	(1.946)	(0.937)
Observations	2,941	2,941	2,941	2,941	2,941	2,941	2,696
Adjusted R^2	-0.0005	-0.0004	0.002	-0.001	0.001	0.001	0.0002
Residual Std. Error	1.411 (df = 2936)	1.483 (df = 2936)	1.882 (df = 2936)	1.680 (df = 2936)	1.563 (df = 2936)	1.493 (df = 2936)	2.302 (df = 2691)

Table 10 Daily Stock Returns and Air Pollution: Hong Kong

The table presents summary reports for Model (2) with sample period 2000-2016. t-statistics are stated in parentheses. *, ** and *** represent significance at the 10 %, 5 %, and % level, respectively. Note: Oil & Gas sample begins in 2005.

	Dependent variable: Daily Index Returns (r_t)					
	HangSeng (1)	Utilities (2)	Financial (3)	Industrial (4)	$OilGas^{cacl}$ (6)	$OilGas^{HS}$ (8)
$Unhealthy_{t-1}$	-0.109	-0.087	-0.110	-0.072	0.128	0.110
	(-0.972)	(-1.170)	(-0.969)	(-0.552)	(1.030)	(0.395)
jan	-0.126	-0.064	-0.228^{**}	-0.065	0.018	-0.029
	(-1.362)	(-1.054)	(-2.446)	(-0.609)	(0.170)	(-0.163)
mon	-0.065	0.019	-0.098	-0.041	0.122^{*}	-0.270^{**}
	(-1.065)	(0.481)	(-1.600)	(-0.580)	(1.799)	(-2.452)
r_{t-1}	-0.013	-0.096^{***}	-0.020	0.011	0.062^{***}	0.028
	(-0.819)	(-6.119)	(-1.295)	(0.716)	(3.805)	(1.043)
Constant	0.044	0.039^{**}	0.062^{**}	0.033	0.177^{***}	0.031
	(1.567)	(2.131)	(2.180)	(1.012)	(5.620)	(0.619)
Observations	4,014	4,014	4,014	4,014	3,773	1,404
Adjusted R^2	0.0002	0.009	0.002	-0.001	0.004	0.002
Residual Std. Error	1.521 (df = 4009)	1.002 (df = 4009)	1.533 (df = 4009)	1.765 (df = 4009)	1.652 (df = 3768)	1.637 (df = 1399)